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Optimisation of energy management in commercial buildings with weather forecasting inputs: A review

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ABSTRACT

Information about the patterns that govern the energy demand and onsite generation can generate significant savings in the range of 15–30% in most cases and thus is essential for the management of commercial building energy systems. Predominantly, heating and cooling in a building as well as the availability of solar and wind energy are directly affected by variables such as temperature, humidity and solar radiation. This makes energy management decision making and planning sensitive to the prevalent and future weather conditions. Research attempts are being made using a variety of statistical or physical algorithms to predict the evolution of the building load or generation in order to optimise the building energy management. The response of the building energy system to changes in weather conditions is inherently challenging to predict; nevertheless numerous methods in the literature describe and utilise weather predictions. Such methods are being reviewed in this study and their strengths, weaknesses and applications in commercial buildings at different prediction horizons are discussed. Furthermore, the importance of considering weather forecasting inputs in energy management systems is established by highlighting the dependencies of various building components on weather conditions. The issues of the difficulty in implementation of integrated weather forecasts at commercial building level and the potential added value through energy management optimisation are also addressed. Finally, a novel framework is proposed that utilises a range of weather variable predictions in order to optimise certain commercial building systems.

Contents

1. Introduction

As a response to increasing electricity prices and greenhouse gas emissions, a variety of measures are being adopted by a growing number of commercial buildings. Such measures are aiming to either generate energy onsite or manage the demand via energy efficient designs, upgrades and demand response (DR) policies; often a combination is present. These energy systems are subject to high degrees of optimisation in terms of financial savings as the value of energy is variable and affected by a range of factors, such as the time of day, season and the energy source. Hence, there is a substantial research aiming to achieve optimal energy performance of commercial buildings. Ideally, during

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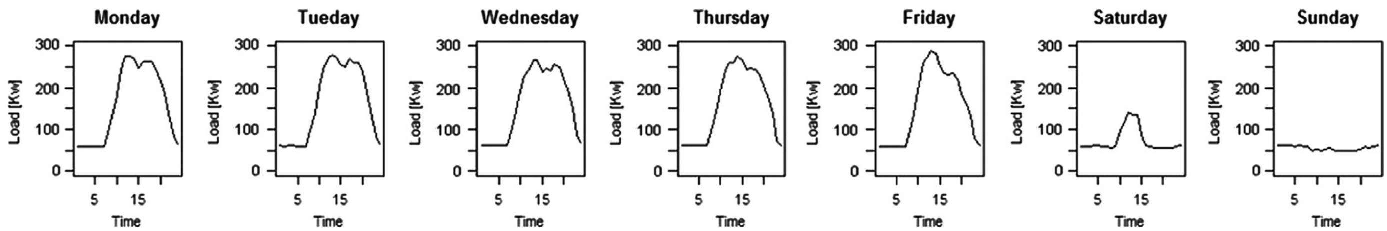
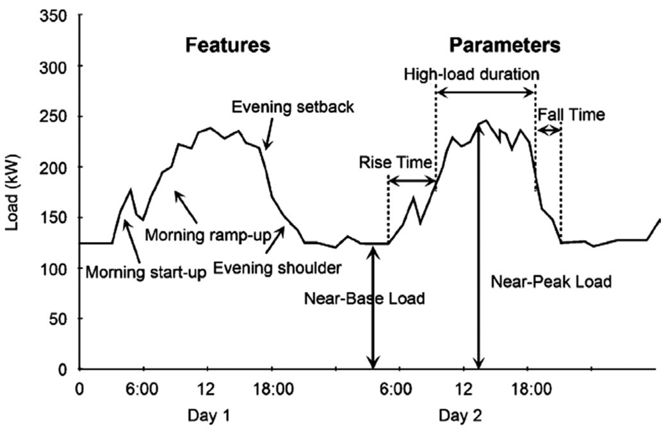


Fig. 1. Average weekly load over 2009 for a university building with a large HVAC system in Spain [87].



Load Shape Parameter	Definition
Near-Base Load (kW)	2.5^{th} percentile of daily load.
Near-Peak Load (kW)	97.5^{th} percentile of daily load.
High-Load Duration (hrs)	Duration for which load is closer to near-peak than near-base load.
Rise Time (hrs)	Duration for load to go from near-base load to start of high-load period.
Fall Time (hrs)	Duration for load to go from end of high-load period to near-base load.

Fig. 2. Commercial load profile features on a typical weekday [2].

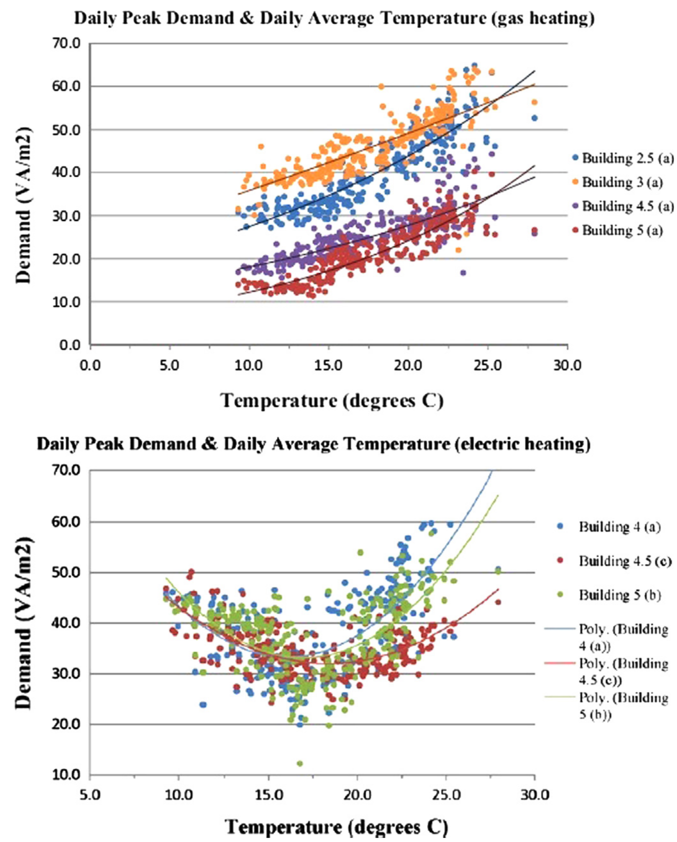


Fig. 3. Correlation of daily peak load and average temperature for electrical conditioned and gas heated commercial buildings in Sydney [5].

periods of high energy cost, consumption should be minimised and generation, where available, should be maximised. Thermal or electrical storage are frequently used as energy buffers and regulators of demand during the day. The key to such optimisation algorithms is analysing the system's behaviour and predicting its evolution as accurately as possible on a rolling horizon of some minutes up to several days ahead, so that generation and demand can be matched and produce the maximum potential savings.

Commercial building loads are distinctive as they generally vary in regular diurnal, weekly and seasonal patterns. Moreover, they are to a large extent related to the weather and provide grounds for optimisation as long as the governing patterns are well understood [1]. On a daily basis, notable similarities appear between typical commercial building energy profiles: the presence of a base load, a morning ramp-up, an afternoon peak followed by a "shoulder" and finally an evening recession towards the base load [2]. Weekend load profiles are usually reduced in magnitude. A typical commercial building weekly load can be seen in Fig. 1. Mathieu et al. proposed a characterisation of the features of a regular weekday commercial energy consumption profile, which is displayed in Fig. 2. Depending on the local climate, prominent variations may be observed between seasons. Typically, major efforts have been made in predicting and optimising the thermal aspects of building energy systems, because heating, ventilation and air conditioning (HVAC) accounts for the largest part of the overall energy demand in commercial buildings [3,4]. Evidence also shows that HVAC is majorly responsible for the magnitude of peak loads [5]. Total and peak HVAC loads are predominantly affected by the prevalent weather conditions. The dependence of peak load on temperature for a range of commercial buildings in Sydney is illustrated clearly in Fig. 3. Additionally, distributed generation (DG) from renewable energy sources (RES) are inherently tied to the weather. Therefore information about the evolution of weather variables are valuable input data for optimisation algorithms.

Both residential and commercial loads are equally significant contributors to the energy consumption mix globally. Compared to residential building loads, commercial load energy management has certain features that are drivers for research in the field of forecasting and optimisation using weather variable inputs. The main reasons for focusing on commercial buildings in this review are summarised in Fig. 4. These reasons have resulted in the development of a multitude of approaches to load forecasting and energy management [3]. Zhao and Magoules [6] reviewed the recent trends in forecasting building energy consumption with particular emphasis on machine learning techniques. Foucquier et al. [7] complemented their effort by expanding the list of algorithms that appear in the literature, comparing and classifying them. Another recent effort by Sun et al. [8] focused on examining methods of shifting peak load in buildings.

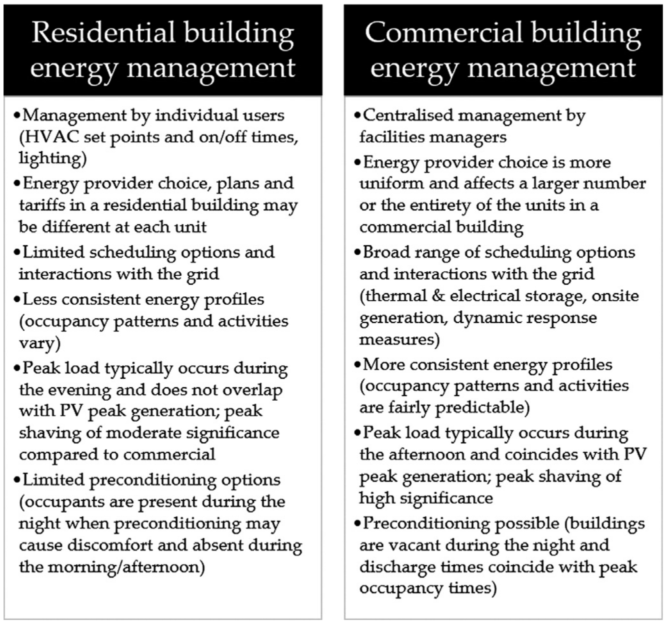


Fig. 4. Comparison of residential and commercial building energy management features that are relevant to weather variable based optimisation.

With the realisation of the importance of weather variable inputs in the energy management of commercial buildings, this paper attempts to review methods for prediction of weather variables and discuss their contribution to the prediction of generation and load, as well as the potential to add value to building energy management. The first section deals with studies dedicated to locally predicting temperature or other relevant weather variables for purposes of building energy management. Generation and load prediction methods that use inputs from local or external weather forecasting are reviewed and assessed in the following sections. Finally, the outputs of the aforementioned methods are serving as inputs for optimisation algorithms, which are discussed in the last section. The rationale behind this sequential layered structure serves the aim of linking the forecasting techniques proposed in the literature to a holistic energy optimisation framework based on weather variable inputs.

2. Forecasting techniques

Before proceeding to the discussion of the applications of weather, generation and load forecasting in the energy management of commercial buildings, it is deemed necessary to present and compare the features of the most common groups of forecasting techniques used in the literature. Broadly speaking, forecasting can be classified into statistical, machine learning and physical methods. Hybrids are not uncommon in the literature, as each group contains features that can complement each other and improve forecasting quality.

Statistical forecasting approaches are based on analysing a set of data points in a time series of the variable in question. The time series regression can be used to forecast the future values of a particular variable. In addition, it is possible to correlate the input variable to output variable for instance ambient temperature to building load. Typically, statistical methods function best for short horizon predictions. Linear regression (LR) is a simple statistical approach that attempts to correlate an output variable with inputs through multiple linear relationships of appropriately weighed coefficients. However, most commonly forecasting techniques are based on the Box–Jenkins methodology [9–11] and combine an autoregressive (AR) and a moving average (MA) model. The AR and MA parts are responsible for linking the present value of the time series to its past values as well as some past random error respectively. When there is an integrated part added to ARMA methods, which allows removing any non-stationarity from the data [12]; in such cases the models are referred to as ARIMA. The AR family is capable of simulating the processes that govern the evolution of variables that are subject to randomness (stochastic forecasts).

Stochastic forecasts are often combined with deterministic models that can predict the evolution of variables that are independent of random error. Exponential weighting (EW) is an example of such a technique. The principle of EW approaches is assigning appropriate weights to observations in a time series in order to develop forecasts for future points. The Holt–Winters (HW) approach [13,14] is of particular interest to energy consumption forecasting as it accounts for seasonality patterns in a time series that are linked in an additive or more commonly in a multiplicative manner. The presence of seasonality in variables such as ambient temperature or load allows the use of Fourier time series as an alternative method to approximate the wavelike behaviour of the variable.

A different approach in forecasting is realised in the form of algorithms simulating learning processes, mainly in the form of neural networks (NN). Rather than using the input data to decompose the time series and develop a fit using a number of parameters, NN attempt to simulate the non-linear and non-stationary univariate or multivariate dependences through networks similar to those found in the central nervous systems of mammals. The network consists of layers of nodes that form a number of staged connections of different weights between inputs and outputs. Training data are fed in the input layer and evolve as they propagate towards the output layer to match the actual data as closely as possible. This is mainly achieved by an algorithm known as back propagation; the parameters of each node are being continuously modified according to a stream of feedback that flows backwards and describes how accurate the configuration is compared to the target results [15]. Support vector machines (SVM) are promising machine learning alternatives utilised in forecasting in the context of commercial buildings. SVM attempt to model non-linear relationships based on a structure risk minimisation principle that aims to minimise the upper bounds of error of the object function. Their distinct advantage over NN is the ability to locate global minima rather than local minima in the solution space as well as the ability to solve non-linear systems with a smaller training dataset [16].

Physical forecasting methods are based on attempting to mathematically model the physical processes that characterise a system in order to predict its future state. In the case of buildings, the physical processes typically include both its structural and thermodynamical aspects, as well as interactions with its internal and external environment. While historical data are typically not required, the amount of inputs differs from case to case. Hence there are varying degrees of parameterisation and complexity of physical models. According to the amount of details known and accounted for, physical models are known as white box for high number of inputs or grey box for a lesser amount of inputs. For buildings, these techniques often allow the development of thermal networks analogous to an electrical circuit, representing the building after determining values of the heat sources (internal appliances, occupants and solar radiation), thermal resistors and capacitors (building envelope elements).

When forecasting is concerned with the weather rather than building thermal behaviour, it is often referred to as numerical weather predictions (NWP). Numerical methods rely on the analysis of the evolution of a set of variables in the atmosphere

Table 1
Comparison of forecasting techniques.

Forecasting family	Method	Features	Major limitations	Example studies
Statistical	Autoregressive moving average models (ARMA and ARIMA)	Simple, fast, relatively high accuracy, ability to account for seasonalities to some extent, short forecasting horizons	Historical data are needed, weak in modelling non-linear patterns	[16–28]
	Autoregressive models with exogenous inputs (ARX)	As ARMA, with enhanced ability to account for recent exogenous changes	As ARMA, plus require availability of exogenous variable monitoring	[29–34]
	Linear regression (LR)	Simple, fast, fair accuracy	Weighing of coefficients is challenging, weak in modelling non-linear patterns and seasonalities	[27,34–37]
Machine learning	Artificial neural networks (NN)	Accurate, no need for supervision, able to model non-linear patterns, high running speed	Reliance on historical data, computationally complex	[26–28,30,38–63]
	Support vector machines (SVM)	Accurate, more solid architecture than NN, able to model non-linear patterns, needs less training data than NN	Computationally complex, low running speed	[16,64–69]
Physical and numerical	Engineering white and grey box methods	Highly accurate, do not rely on historical data, physical interpretation	Multiple inputs needed, can be complex and slow running speed	[8,70–90]
	Numerical weather prediction (NWP) and physical weather forecasts using external inputs	Highly accurate, do not rely on historical data, physical interpretation, long forecasting horizons	Uncertainty present, resource intensive and time consuming, low temporal resolutions if external data are used	[91–95]

in a multidimensional calculation space, governed by equations of the thermodynamics, fluid dynamics and chemical reactions of the constituents of air. They function best for horizons of some hours to days ahead. Obtaining consistently accurate weather forecasts of high temporal and spatial resolution via numerical methods is relatively impractical and computationally complex for commercial buildings. As such, until recently NWP applications for commercial building energy management have not been extensively researched.

Forecasting algorithms have evolved in the last two decades to a point where they can predict the future state of the relevant variables with high degrees of accuracy for a range of applications in building energy management. While different metrics are being used for the evaluation of each algorithm depending on the application, prediction errors are generally within acceptable ranges.

Statistical approaches are simple in terms of implementation, demonstrate high simulation speeds and require low computational power. However they are challenged when trying to interpret non-linear relationships and rely heavily on consistent historical data. Machine learning techniques are considered as an alternative able to capture non-linear relationships without manual estimation of the parameters. Nonetheless, the complexity of such algorithms is high and the reliance on reliable and large amounts of archived data is still present. In addition, unique problems such as overfitting to the training datasets may arise. Physical forecasting methods attempt to analyse the underlying principles that govern the system, rather than trying to “guess” the input–output relationships. Parameterisation of physical models poses a challenge and in many cases estimations have to be made according to the availability of inputs and required complexity. A summary of the features of the different groups of forecasting approaches and the most commonly used examples found in the literature related to commercial building energy management can be seen in Table 1.

3. Weather variable prediction

Many of the operational traits of the buildings and behavioural aspects of occupants are inherently correlated with weather variables. Solar and wind power generation, HVAC load patterns and to a certain extent lighting load and occupancy habits are predominantly affected by the ambient temperature, humidity, incident solar radiation, cloud formation and sometimes wind [17]. Weather is perceived as the result of numerous interactions between the atmosphere and the surface of the Earth and since it is difficult to obtain information about the state of every particle participating in those interactions, typically data assimilation is conducted via spatially and temporally scattered observations [18]. Forecasts about weather variables can be acquired via statistical or physical means. In this section a range of weather forecasting applications for energy management purposes are reviewed.

An early attempt to predict ambient temperature with an ARIMA model for purposes of cooling load forecasting has been developed [19]. An ARMA model was decomposed in a stochastic part and a deterministic EW model to predict ambient temperature and its accuracy was reported to improve by almost 10% [20]. A similar method of conducting temperature forecasts for load prediction in buildings via a combination of deterministic part and a stochastic ARMA part has also been implemented [21]. The technique was extended to predict humidity and solar radiation using a Fourier time series for the deterministic part [22].

More often predicting the internal temperature, rather than ambient temperature is of interest for building energy optimisation. Mustafaraj et al. [23] modelled and compared a range of statistical models with or without external inputs for predicting internal temperature and humidity, and it was concluded that the ARMA outperformed the ARX model for temperature, but in order to produce accurate humidity forecasts higher complexity AR models were required. ARX models were used with a range of external weather variable inputs to predict the temperatures of monitored classrooms in a university building [24]. It was reported that only recent external variable observations of no longer than 15 min affected the temperature, otherwise a simple AR model is sufficient.

In addition to temperature, solar radiation is often considered in relevant research and was forecasted using historical data and validated for modelled buildings [25]. Furthermore, local solar radiation was predicted via a deterministic EW technique [20]. A different approach through simulation of the atmospheric state in MATLAB was proposed [26]. A multiple LR technique for short

term solar radiation forecasting for buildings was implemented by Zhang and Hanby [27] using a combination of onsite observations and third party weather forecasts.

Approaches based on NN of different architectures have been carried out to predict ambient temperature patterns for short term horizons [28] or internal temperature in selected zones of commercial buildings [29–32]. Integrated multivariate weather forecasting modules based on NN have also been developed [33,34]. It was found that higher accuracy is obtained when multiple zone interactions are considered in internal temperature prediction [35]. Another type of NN was developed by Ferreira et al. [36] and included in a sensor that directly obtains and analyses data of temperature, solar radiation and cloud coverage. Common elements of these algorithms include the necessity for onsite weather observations and an indexing method associating these values to particular times, days and seasons. The use of NN over statistical methods is preferred due to their ability to capture non-linear patterns in the evolution of weather variables [37]. In another study the operative temperature inside a building was found to be predicted 9% more accurately with NN than ARX [38]. Improved performance has been observed when NN were hybridised with statistical approaches, such as ARMA to forecast solar radiation after removing non-stationarity from the time series [39]. It should be noted however, that the added complexity and costs of NN compared to simpler statistical approaches are often not justified by the boosts in forecasting performance [37].

The uncertainty related to weather variables imposes a challenge to predictions of longer horizons. Furthermore, certain events such as the formation of clouds or gusts of wind are not easily predicted via purely statistical approaches. However, such phenomena can be modelled with higher accuracy via NWP models. For instance, outputs from a NWP model (Weather Research and Forecast Model) were produced and used to develop an ensemble of forecasts in order to account for the sensitivity of weather to the initial conditions and their inherent uncertainty [18]. It was argued that the NWP is more accurate and thus valuable than the statistical model, especially for horizons longer than 8 h. It can be seen in Fig. 5 that even though the statistical approach was able to predict the temperature trends, the fact that it deviates notably from the actual observed values undermines its applicability to building management algorithms [18]. On the other hand a NWP ensemble was able to add value to the forecasts by minimising the error consistently for the 5 day horizon. The thermal mass of the building responds in long time frames, thus NWP methods are indeed superior for these horizons. Similar conclusions confirm the superiority of NWP to statistical time series models, as the standard error was reduced notably for temperature, radiation and wind predictions; however statistical models were proven effective for short term horizons [40].

Rather than committing resources to generate weather forecasts, Kwak et al. [41] used readily available weather forecasts from the Korean Meteorological Administration and developed their own numerical model for solar irradiation on a case study office building. This allowed for higher temporal resolution and more flexible predictions. In a similar manner, raw real time weather observations from the Hong Kong Observatory were obtained and fed into modules able to process and generate more relevant information for the building, such as solar heat gains, relative humidity and localised temperature evolutions [42]. External weather forecasts have been also combined with onsite observations to produce temperature and humidity forecasts for building control purposes [43].

In addition to hours or days ahead horizons, there have also been studies that attempt to predict the long term effects of climate changes in the energy consumption of commercial buildings [44]. Van Paassen and Luo [45] developed a statistical weather generator model that can be applied towards that end. Another statistical approach was based on generating weather simulations from existing data and utilising them for long term load predictions [46].

Weather variable forecasting and especially temperature forecasting forms the foundation layer of an energy management

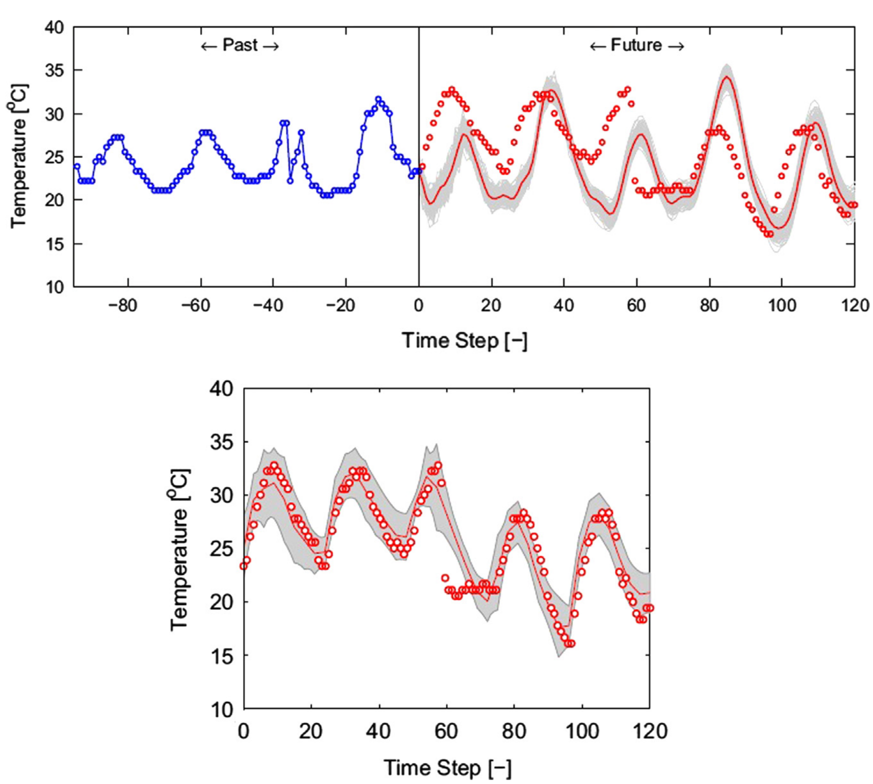


Fig. 5. Comparison of performance of a statistical Gaussian prediction model (top) versus a NWP model (bottom) in 5-day horizon temperature forecasts [18].

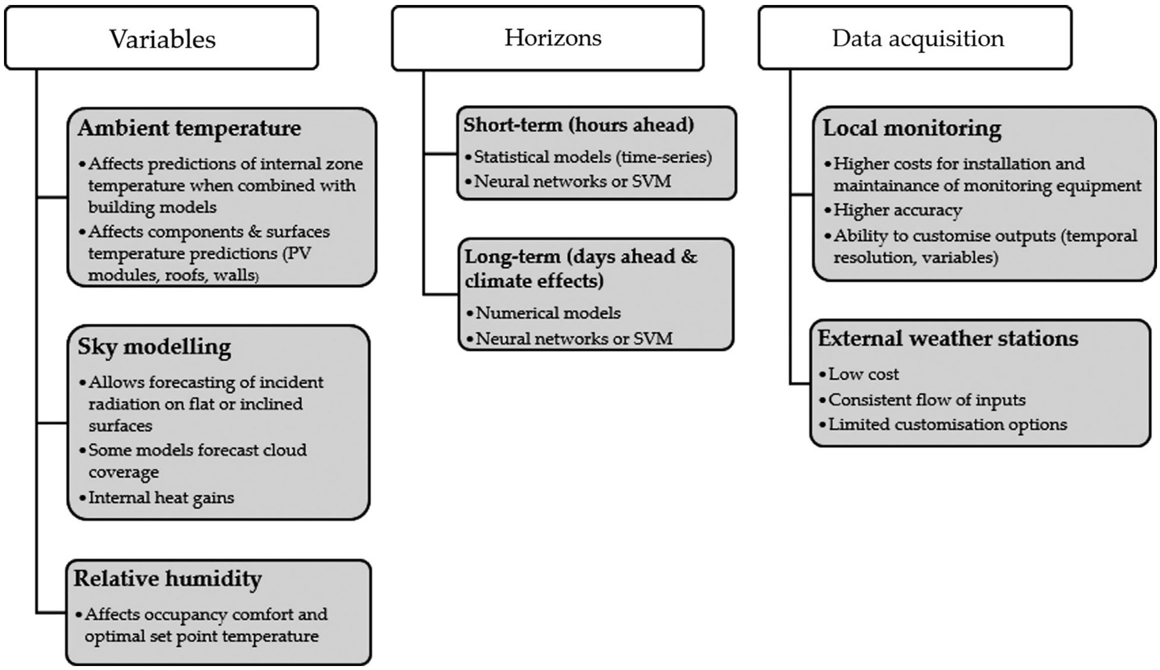


Fig. 6. Summary of key research topics discussed in existing literature in the field of weather variable prediction for building energy management.

framework, yet it is inherently difficult to minimise uncertainty errors. Any forecasting errors propagate to higher level predictions and are possibly magnified as weather variables function as inputs for most of the techniques discussed in the next sections. Due to constraints on data and resources, weather forecasting for purposes of energy management in commercial buildings is commonly obtained from third parties. However, localised forecasting as described in this section offers a range of benefits: the ability to better capture the microclimate of the building, tailored and outputs of data that can be fed directly into integrated optimisation frameworks and customised temporal resolutions. NWP models provide the highest capacity to minimise uncertainty, especially for horizons of some hours up to days ahead. For shorter horizons that are of significance for DR measures in a commercial setting, statistical or NN approaches with external outputs seem to be superior. External outputs allow assigning heavier weights to recent observations of the weather variable in the time series, taking into account the trend of weather conditions to persist and evolve smoothly over time [47]. As such, there is basis to argue that integrated hybrid statistical and numerical weather forecasting models can function as a flexible technique to provide weather variable inputs for energy management in commercial buildings. With this kind of tailored information in hand, predicting the generation from RES is significantly simplified. Fig. 6 summarises the main points examined by the literature in the field of weather variable forecasting for use within building energy management.

4. Generation forecasting methods

The penetration of DG, such as solar panels, wind turbines, cogeneration, fuel cells or other types of batteries in commercial buildings introduces a new challenge in forecasting. In the case of cogeneration and batteries, the generation can be adjusted at will and therefore optimisation algorithms are mainly concentrating on the forecasts of energy costs. However, with intermittent energy sources such as solar radiation or wind power, forecasting the availability of energy constitutes a major aspect of commercial building energy management.

In terms of solar power generation, which is the renewable energy form with the highest penetration in commercial buildings, there is a variety of forecasting software applications that can provide accurate estimates for generation over certain periods of time. Based on models that take into account solar radiation data, system specs and efficiencies, these methods are very effective in predictions of the system's overall performance. However, they fail to capture the solar generation in real time or short horizons, thus they have limited uses for smart-metering or DR purposes [48].

Forecasts of real-time and short term power output of photovoltaic (PV) systems are much more valuable for commercial building energy management. Recurrent cloud formation patterns have been recognised as being notoriously difficult to predict and since the power output of PV system is directly proportional to the incident sunlight, this poses a challenge to forecasting attempts. Such a stochastic ARIMA model for cloud coverage was partially successful [49].

Exogenous weather inputs have been reported to improve the accuracy of generation forecasts. An ARX model with NWP temperature inputs for online solar PV generation prediction was proposed by Bacher et al. [47] and demonstrated significantly improved accuracies by 35% compared to the persistence model. The model was expanded to incorporate NWP inputs for online solar thermal generation predictions with similarly high accuracy [50]. For both cases, it was reported that NWP were most useful in horizons longer than 4 h up to several days ahead, while the AR part was sufficient for short term generation forecasting. This is in alignment with the findings from the weather variable prediction section. ARX has been used in a different study and improved the AR reference model by 13% [51]. A LR method for long horizon PV power generation has been carried out with ambient temperature and solar radiation as exogenous inputs and reported mean monthly errors of as low as 5% [52]. A range of NWP outputs were used in [53] as input to a NN for the real-time prediction of PV solar power and produced average forecast accuracies of 90%. A NN approach to real-time power generation forecasting has been implemented with weather data as the inputs and it was shown that it could generate forecasts of up to 30 min ahead with notable accuracy within the 95% confidence intervals [54]. Furthermore, a range of statistical models with weather

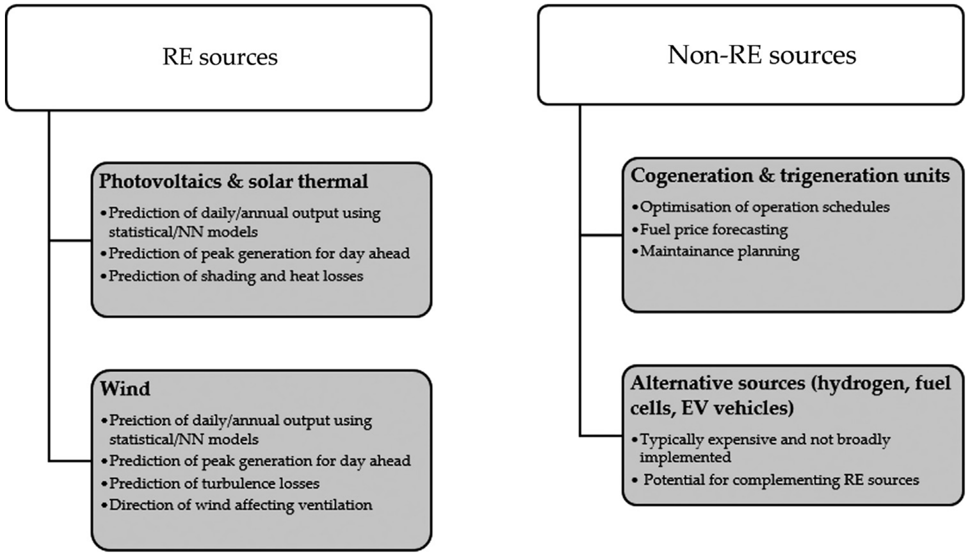


Fig. 7. Summary of key research topics discussed in existing literature in the field of DG forecasting in commercial buildings.

inputs for generation prediction were compared and it was found that the genetic algorithm technique, based on evolving a set of solutions in the objective space outperformed the rest [55].

Instead of using NWP outputs, third party weather observations were obtained and used for the prediction of solar generation via an ARX framework. It was shown that it produced 15% higher accuracy than a non-adaptive NN [56]. Additionally, NN of different architectures with no weather inputs at all have been designed and used for power forecasting [57].

The constraint of an algorithm that is easy to use, fast and not demanding in computational resources applies in energy availability forecasts for commercial buildings. Di Piazza [58] showed that using a statistical *k*-clustering algorithm it is possible to post process raw data from small scale wind and solar installations and achieve relatively high accuracy with as low as 50% of the original data.

Solar based generation (PV or solar thermal) is by far the main topic of generation forecasting literature. While wind energy has limited contribution in the DG mix and non-RE DG sources are not strongly affected by weather variables, they are still discussed in terms of optimisation of the energy management in commercial buildings. An outline of the findings of the reviewed literature can be found in Fig. 7. Information about the availability of energy in the future from any DG sources augments the value of the energy generated, since it can assist with peak shaving, load scheduling and DR implementations. Hence, the savings potential from generation in buildings increases with accurate forecasts. The main variables associated with solar generation (solar radiation) and wind generation (wind speed) are not primarily favoured in load forecasts and consequently there is a conflict for resources. Additionally, since not all buildings are designed with DG capacity, the integration of such forecasts in existing building management systems may prove too costly and complex.

5. Load forecasting

In most commercial buildings, historical load data is readily available. As a result, load forecasting for both short and long horizons is favoured over weather or generation forecasts. The simplest models treat load as a time series by itself, without any correlation to weather outputs. However, it is common to use externally or locally generated weather inputs in order to enhance the accuracy of load prediction for commercial building energy management.

Statistical methods have been broadly used in the literature for load forecasts. There is a multitude of statistical approaches depending on the application, required accuracy and resolution, however the typical approach is to use archived data to generate a function that fits the load data as accurately as possible. For the energy management of commercial buildings short term load forecasting (STLF) is typically of higher priority. Generally speaking, the variables associated with weather and load are changing smoothly and slowly over short periods of time. Using historical load data to develop statistical algorithms is a common practice in order to produce forecasts for horizons up to 6 h ahead [59]. As Mathieu et al. [2] showed, demand response (DR) measures implicate significant potential for savings if applied timely. Ambient dry bulb temperature is recognised as the primary contributing variable to commercial building loads [60], now a commonly accepted fact in load prediction related research.

Electrical and heat loads have been also predicted using LR and generalised long-term profiles for different types of buildings [61]. Fernandez et al. [62] tested a prediction algorithm with a polynomial of varying degree with hourly data from a university building in Spain, but found it can be improved if AR models were applied.

A standard method for modelling the load time series for STLF is based on EW techniques. The original HW model is based on three components: level, trend and seasonality [12]. The exponential weighting can be complemented by a moving average (MA) part as well as ambient temperature dependencies [63]. Taylor applied double and triple exponential smoothing in order to capture additional seasonal patterns in electrical loads [59,64,65], however the algorithms have not been thoroughly tested on case study buildings. Towards the opposite direction of simplifying the model by modifying the level and removing the trend component, He and Zhang [66] validated their approach by forecasting the AC load of an office building.

An alternative statistical method based on historical data that is undeniably more popular in building STLF is the AR family. Predictions of HVAC loads for commercial buildings based on ARIMA algorithms have also been applied [67]. Fernandez et al. tested an ARIMA model [62] and then improved it by introducing a variable learning window mechanism that accounts for days of the same type (weekdays, weekends) and using weight factors to

magnify the importance of the most recent observations in the time series [68]. Hybridisation of AR with other statistical or machine learning methods is not uncommon in the literature. Xuemei et al. report that the errors of an ARIMA algorithm were reduced by roughly 50% by post-processing the outputs with a SVM model in predicting the cooling loads of a commercial building [16]. The improved performance of the hybrid statistical and SVM model over both its individual components can be seen in Fig. 8. Similar results were achieved by the authors in an effort to hybridise an SVM and a genetic algorithm model as the error was reduced by almost 15% [69]. A hybrid model with LR and ARX has been also implemented using indices and succeeded in minimising the size and complexity of the dataset [70]. Gould et al. [1] expanded the established approaches of forecasting via ARIMA or EW by developing a multiple seasonality model with the extra capacity to capture seasonal cycles in the time series. The algorithm was tested on utility data, however it could potentially apply to commercial loads as well.

Another interesting statistical approach was that of Frank and Sen [71], in which peak and overall loads of certain buildings were calculated based on an algorithm that manipulates data in Energy Databases, rather than utilising on site measurements. Finally, a more complex, yet effective method that is able to better capture the non-linear correlations between temperature and commercial building load based on Fourier series has been discussed in the literature [72,73].

An increasingly popular group of load forecasting methods involve the use of NN. Network parameterisation is highly variable and depends on the architecture proposed in each study. The energy demand is expressed as a time series depending on a variety of inputs. Regarding weather components, most often the inputs that are considered are temperature or humidity [74–76]. An example of the framework of a NN model utilising both archived weather observations and rolling weather forecasts is shown in Fig. 9. Regarding commercial building load, there is no consensus as several algorithms have been tried and demonstrated

Predictor	Evaluation indices		
	RMERR (%)	MARERR (%)	RMSRERR (%)
SARIMA	0.89	4.26	11.44
SVR	0.79	3.23	9.64
Hybrid	0.52	2.14	4.58

Fig. 8. Comparison of accuracy of SARIMA, SVM and their hybrid model for the prediction of cooling load of a commercial building in China [16].

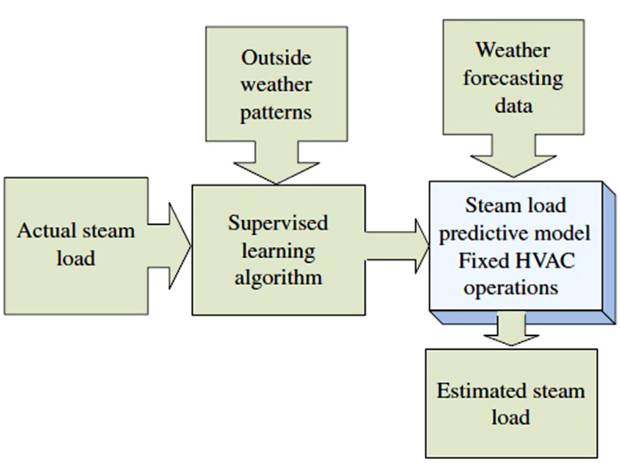


Fig. 9. Steam load prediction framework using a NN with inputs of archived load and weather data as well as weather forecasts [79].

superior performance in correlating weather and time inputs with load outputs. Examples of networks include simple back-propagation NN [76,77], multiple perceptron architecture [78–80], general regression architecture [81], hybridisation with rough sets [82], real-time adaptive NN with dynamic structure [83], recurrent NN emphasising on load dependencies on time [84] and NN with global solutions [74]. An algorithm based on NN has also been used to predict the occupancy heat generation, which in turns affects the building's HVAC loads [85]. The methods display a range of differences in the approaches taken to acquisition of data and pre-processing, training, weighting and post-processing. Nevertheless, the similarity among most NN is the need for extensive historical data and specificity to the training data, but in a number of comparative studies the load prediction accuracy is notably higher than statistical methods [62,86,87]. Nevertheless, NN have been used for HVAC load forecasting in combination with ARIMA and LR models after being weighed accordingly using an hierarchical process [88].

Techniques based on SVM are often treated as superior to NN, due to their advantages discussed in Section 2. The parameterisation of the SVM model impacts its accuracy and has been done via swarm particle optimisation algorithms [89,90] or data clustering [91]. In their papers, Fernandez et al. [62,87] concluded that a 10 dimensional SVM model clearly outperformed a NN model with a hidden layer of 10 neurons in terms of forecasting accuracy. In addition the NN design and parameterisation poses a greater challenge. The improved performance of SVM over NN in predicting commercial loads has been also confirmed in other studies [92,93].

Physical methods often find application in HVAC load forecasting of commercial buildings and are commonly part of a broader optimisation framework. Powerful simulation software suites that are based on physical methods include Energy Plus, DOE-2 and TRNSYS [94–96], but lightweight computer modelling algorithms have been proposed as well, [97,98]. Energy simulation models have been used to examine commercial buildings' energy profile from various perspectives and to different degrees of detail, thanks to their flexibility and modularity. The models are of interest to researchers, building designers and energy managers and are able to handle archived and real-time load and weather data. They are often used to both enhance the understanding of the building's energy profile and heat transfers as well as offer valuable insight for the design of future buildings [99]. Prediction accuracies using energy simulations have been reported to be rather good in certain cases, as high as 99% for the prediction of HVAC loads [100,101]; however, there are also limitations for instance when predicting solar heat gains [102]. There are additional inherent challenges associated to complex occupant behaviour and the poor evaluation of equipment performance. Nevertheless, in a study by Chua and Chou [103] the simulations managed to accurately evaluate the dependence of HVAC load to certain weather parameters. Combined with statistical methods, energy simulation models have been also successful in generating accurate predictions of load in mixed purpose commercial buildings [104]. Another successful application that is useful for implementing optimised controllers was the prediction of the effects of using blinds for shading via building energy models on building load [105,106].

The parameterisation of the models for conduction, convention and radiation heat transfers has been thoroughly described [107]. The American Society of Heating, Refrigerating and Air Conditioning (ASHRAE) method uses a set of transfer functions parameterised appropriately to convert heat gains into cooling loads and has been featured as the starting point in various research papers for the estimation of commercial building load [108,109]. Rabl and Norford [110] developed an algorithm using physical state equations to describe the thermal behaviour and load of a case study

office building, while recent research [111–113] achieved the same goal through training their model with field data retrieved from various onsite data or external weather data from third parties [114]. A common modelling technique is based on using an electrical circuitry analogy to analyse the thermal behaviour of different zones within a building. In the example of Fig. 10. temperature differences are equivalent to voltage differences, resistors and capacitors represent the thermal resistance and thermal storage capacity of the materials of the building and heat sources are modelled as current sources.

An alternative approach was studied by Luo and Ariyur [115], who included dynamic parameterisation and examined the connectivity between different zones within the same building. Variations in internal heat gains, potentially caused by changes in occupant numbers or stochastic patterns, like leaving doors or windows open were shown to have a significant effect in the HVAC load. The parameterisation of the building thermal network has also been carried out with the help of a genetic algorithm [116]. Using an alternative approach, a non-parametric state model able to predict the thermal load of commercial buildings has also been developed [117].

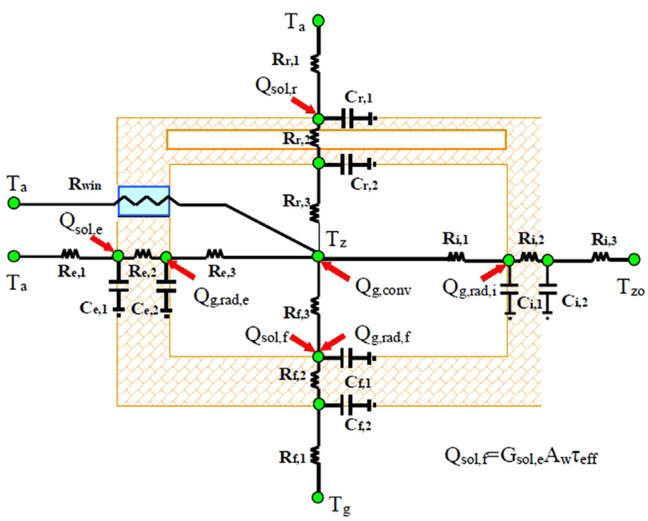


Fig. 10. An RC thermal model used for analysing the thermal response and forecasting HVAC load in a commercial building in Iowa, USA [113].

The states at different locations within a building can be expressed as a function of weather inputs, internal heat gains and structural parameters, which allows the forecast of the future thermal state and thus the energy demand [118]. Similar techniques, where the evolutions of the state and demand of a zone within a commercial building are estimated via thermal networks [119] or thermodynamical and fluid mechanics equations [120] have been proposed. A simplified, yet efficient approach to prediction of cooling load was proposed by Sun et al. [94]; rather than just modelling the thermal performance of a building, a three step algorithm taking into consideration seasonal and weather inputs as well as historical data is implemented and validated in a large commercial building in Hong Kong.

Rather than analysing a commercial building as a single entity, Escrivá et al. [121] proposed energy auditing and performance modelling of individual air conditioning units within a building, the aggregation of which allows for the prediction of the total load.

Physical models can also assist when predictions of the overall load, rather than the peak load are needed. An easy to implement algorithm uses temperature variations to predict cooling (or heating) degree hours and in turn the HVAC load for a building [122].

Regardless of the approach, load predictions serve as inputs for manual and automated decision making in energy management. For STLF, many of the papers reviewed in this section report low errors and superior prediction accuracy. Nevertheless, it shall be noted that for statistical and machine learning methods, the training is implemented using historical data from the case study building. This gives rise to two issues: the ability to adapt to changes in the building is limited, especially for statistical methods and it is not guaranteed that the algorithm can provide consistent results if applied to a different building. Physical models on the other hand are based on established physical laws and equations, which are universal; thus the main hurdle for forecasting accuracy is posed by resource limitations when modelling the system. Hybridisation of models could enhance accuracy, but this raises the complexity. As discussed earlier, locally generated external inputs for load forecasts when available, such as temperature or solar heat gains, also result in improved performance. Consequently, it is suggested that since all families of approaches for STLF demonstrate comparable errors and possess unique advantages and disadvantages, the defining factor for utilisation by a commercial building should be the ability to integrate with an

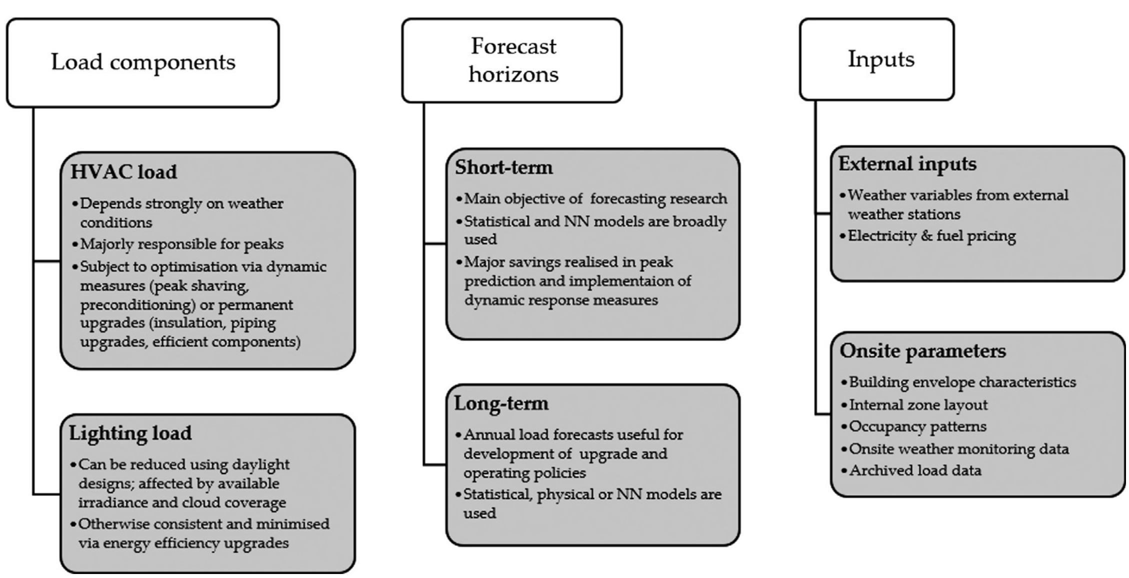


Fig. 11. Summary of key research topics discussed in existing literature in the field of commercial building load forecasting.

optimisation framework. Depending on the size, occupancy patterns, location and stakeholder intentions the chosen optimisation framework should dictate the most appropriate architecture for STLF. The key issues discussed in the relevant literature reviewed above are presented in Fig. 11.

6. Energy management optimisation

Based on the information about the current and future state of weather variables, load or generation, building management systems (BMS) can adjust the set points for HVAC, as well as regulate the flow and consumption of energy within the building or the exchange of energy with the grid. This allows the system to meet DR measures and reduce peak and annual energy consumption and hence minimise energy costs [123]. Stochastic optimisation processes have been proposed and validated with models or site testing in the literature and will be reviewed in this section.

Sets of rules in the form of controllers regulate the parameters of operation of HVAC as well as other components of the load and can integrate the thermal mass or alternative storage sources in many ways. Unlike Rule Based Control, where a set of rules govern the behaviour of the HVAC system deterministically, Model Predictive Control (MPC) is an optimisation framework that seeks an optimal solution to an objective function of load bound to certain constraints (tenant comfort, energy costs and building characteristics). MPC is taking into consideration the future state of the energy system, the capacity of thermal or electrical storage and the interdependencies on weather or occupancy patterns [118]. Often based on real time optimisation (RTO), these strategies can minimise the costs of the system without compromising the comfort of the occupants as a response to external stimuli. This is mainly achieved by exploiting the whole range of the thermal comfort zone throughout the day. External stimuli, such as temperature or solar heat gains are realised in the form of disturbances and integrated in the algorithm in a real-time manner. MPC can be adjusted to optimise the system flows on varying horizons depending on the HVAC capacity and structure of the building [124]. Typically, disturbances are forecasted using methods discussed in the previous sections. MPC demonstrates tolerance to the inherent inaccuracies of the weather and demand forecasts that provide inputs [125]. A flowchart demonstrating a typical MPC architecture as described in [118] can be seen in Fig. 12.

Weather forecasting for MPC mainly incorporate predictions of ambient temperature and sometimes humidity and solar radiation [126]. Such generic inputs are often obtained from external

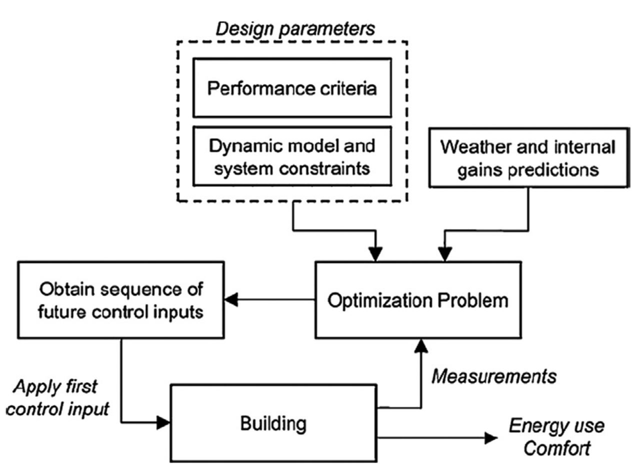


Fig. 12. Example of a MPC framework incorporating weather predictions [118].

meteorological entities. However, several attempts indicate superior optimisation results and increased savings when tailored forecasts of weather and indoor temperature obtained from onsite simulations are used as inputs for MPC [25,42,75,118,127–129]. Zavala et al. [18,40] proposed a modified version of a dynamic RTO framework that incorporates weather forecasts of different horizons and concluded after simulations in a case study large building that higher savings up to 30% can be achieved for one day ahead horizons compared to the base reactive RTO scenario. In fact the savings were found to be even more significant for a modelled building with thicker insulation due to better utilisation of its thermal mass. In addition, the weather component resulted into alleviating one of the main limitations of RTO routines, namely the inability to utilise existing trends in the time series. It can be seen in Fig. 13, that the statistical forecasts resulted in higher error and even in setpoint temperatures outside the comfort zone. On the other hand, NWP predictions helped maximise the savings by matching predicted and actual temperatures and correctly adjust HVAC within the comfort zone. Occupancy comfort is regarded as an equally important objective to energy savings in the optimisation literature. However, as seen in Fig. 14 there is often great margin for improvement. The optimal controller with perfect weather forecasting would achieve the lowest energy costs at the lowest possible discomfort cost. Most conventional controllers though are operating without weather inputs and can only achieve low occupant discomfort at relatively high energy costs. Dynamic RTO with weather inputs are also considered and have been validated via mixed integer linear programing [130] or NN controllers [30,33,34] with reported savings in the vicinity of 25–30%.

In addition to weather inputs, occupancy pattern inputs have been considered. Significant saving potentials have been realised and it has been concluded that weather and occupancy patterns are correlated, hence reducing the degree of complexity of the optimisation problem [131]. Using a numerical analysis it has also been concluded that savings of up to 50% can be achieved with RTO systems in place receiving weather sensitive and occupancy inputs [132]. It has been demonstrated in various control and optimisation routines that using the outputs from a physical load forecasting model and taking advantage of the stored energy in the thermal mass of a commercial building are very effective in generating energy savings for peak consumption by shifting the load to lower cost off-peak zones [133–141] mainly through preconditioning. Lee and Braun [113] studied two such alternative preconditioning strategies to the typical deterministic night setup. It can be seen in Fig. 15 that with preconditioning the daily load overall is not significantly affected, however the peak load is greatly reduced thus leading to savings without compromising the comfort of the occupants. The performance of such controllers can be enhanced by adding real time electricity price feedback to the input mix [142]. Besides assisting with thermal storage strategies and load shifting, weather variable forecasting has been used to adjust solar heat gains via shading controls [143].

An integrated active and passive cooling, ventilation and shading plan has been simulated with the aid of a MPC and achieved significant energy savings of up to 80% compared to the manual control scenario [144]. Additionally, the comfort of occupants was not violated during the simulation period. Dynamic optimisation of HVAC setpoints has also been the subject of a similar algorithm [145]. Moreover, a single zone MPC has been proposed using the outputs from a NN [146]. A design able to generate a real-time model of the case study building's thermal performance and then automate the BMS optimisation processes has been developed [147]. In the controller discussed in another study solar heat gains were modelled thoroughly for the energy management of a passive solar commercial building [148].

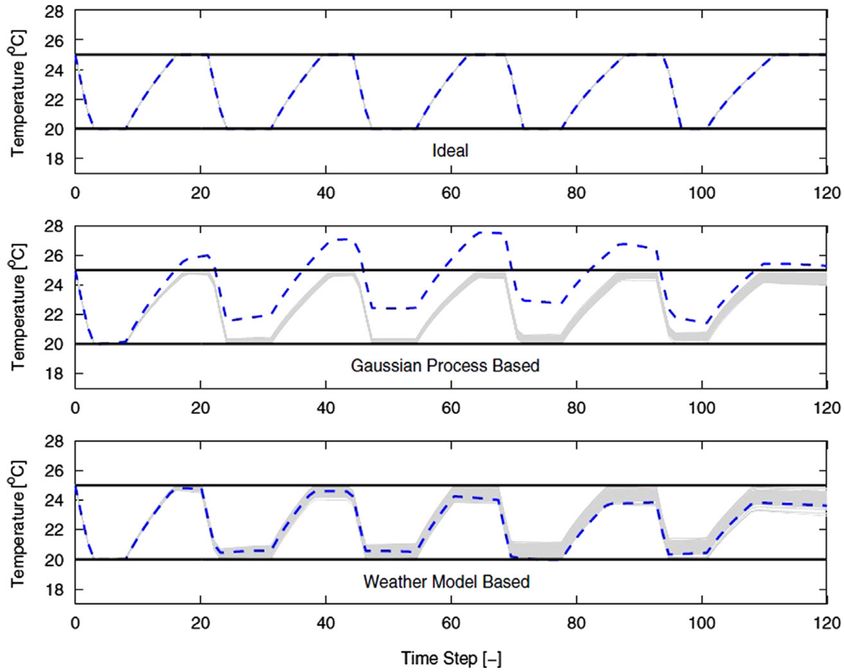


Fig. 13. Comparison of 5-day ahead operating HVAC strategies, with predicted interior temperatures being in grey, actual observations in dashed blue lines and the comfort zone in thick solid lines [18]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

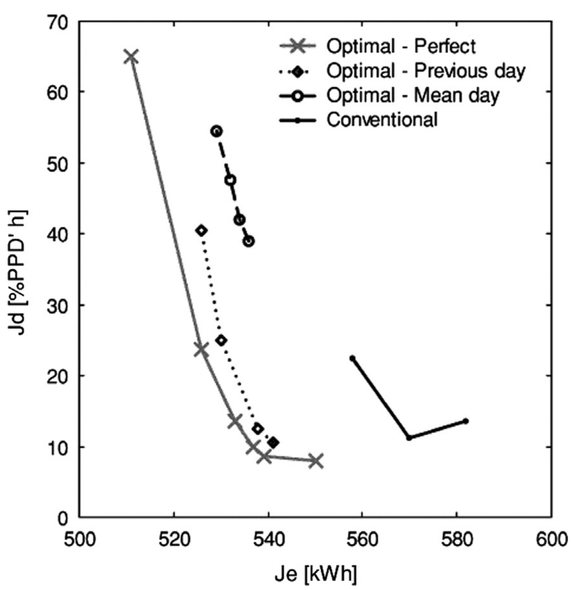


Fig. 14. Correlation of discomfort cost (Jd) and energy cost (Je) for a range of controllers [148].

Certain studies are concerned with the optimisation of individual components of the HVAC load, rather than developing an integrated plan. In a consolidated study [149] a variety of strategies of operation were tested for each component of the cooling system in order to realise the optimal mode. Sun et al. [150] proposed an optimisation algorithm to determine the most effective schedule in starting up chillers in case study office buildings. Other optimisation studies are delving into the control of shading devices, such as blinds and reported savings of up to 50% from the base scenario [105,106].

Optimisation of DG schedules is equally important to demand consumption optimisation. Regarding cogeneration systems able to produce both heat and electricity in commercial buildings,

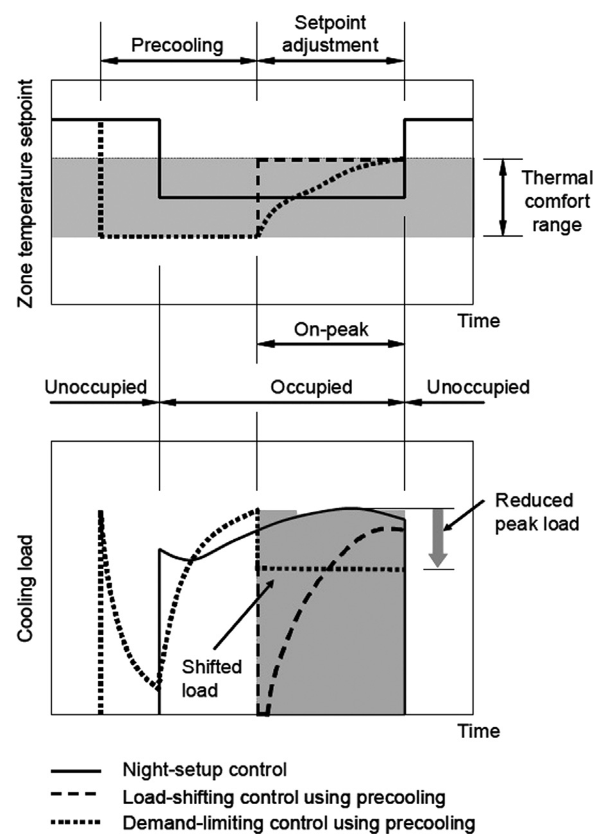


Fig. 15. Effects of deterministic approach versus preconditioning on interior temperature and daily cooling loads [113].

optimisation processes have been proposed using mixed integer linear programming [151]. A network flow model based on the physical operation modes of a cooling, heating and power system (CHP) as well as dynamic states of the grid has been described and utilised for savings optimisation [152], while the same goal was

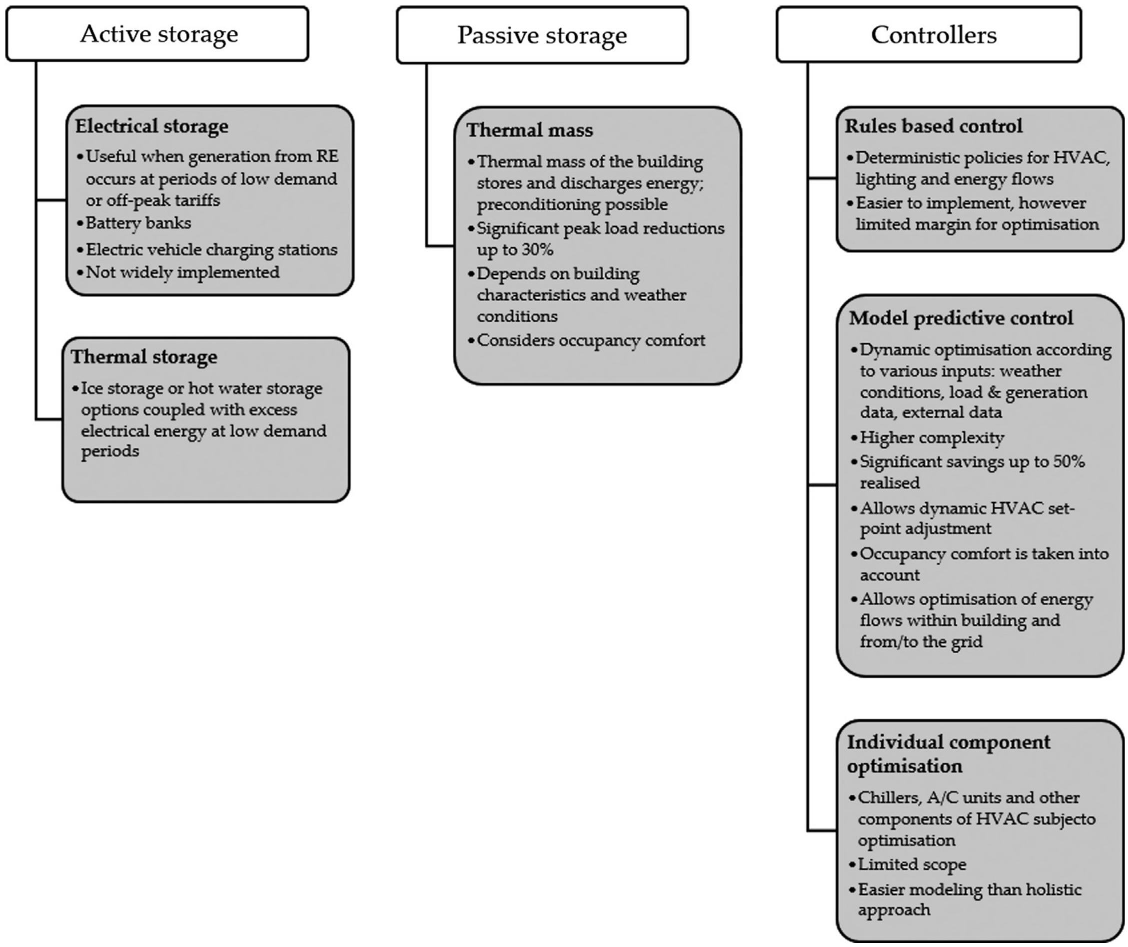


Fig. 16. Summary of key research topics discussed in existing literature in the field of commercial building energy optimisation frameworks.

reached with an even more simplified flow approach [153]. Weather conditions responsible for transient trends in a CHP system have been considered and allowed the development of a predictive control algorithm [154].

When renewable energy sources are part of the DG mix, optimisation problems become more complex due to the intermittent nature of power generation. The controller in addition to optimising load variables according to the predicted states of the system, has to be able to forecast the generation. Since PV generation is strongly affected by weather parameters and especially solar radiation and ambient temperature, such controllers are relying on accurate weather forecasts. For instance, a simple MPC was developed and fed weather data from a local station as well as real-time pricing of energy to optimise the energy flows of a smart research building in Denmark [155]. Optimisation with a controller able to monitor the online solar PV generation has also been developed [156]. Simple controllers that disregard weather inputs can still improve the utilisation of solar PV and thermal systems as seen in a small building case study [157].

Very often, optimisation solely involves electrical or thermal storage in a commercial building. A non-predictive approach has been developed, in which energy storage charge and discharge rates are governed by the feedback generated from previous responses of the system in terms of costs [158]. Batteries can be regarded as additional nodes of DG in a building, whether stationary or mobile. Electric vehicle batteries connectivity to a commercial building have been modelled using a mixed integer linear programme in order to predict and optimise the behaviour of the energy system [159]. In addition, the effects of MPC on buildings with both active and passive energy storage have been demonstrated [160].

Ice storage is an alternative to utilising the thermal mass of a building. The operating principle of ice storage system is cooling water down to form ice during low energy cost times and releasing its latent heat during peak times to provide cooling. As with thermal storage, it is possible to minimise the costs with accurate load predictions. MPC algorithms with distinct emphasis on ice storage have been described [75,137,161,162]. Typically, ice storage optimisation is conducted on a daily horizon, however it was shown that control based on calculations of the load and weather evolution over a weekly period are viable [163].

While there is an extensive array of issues of interest to research, the literature is mainly concerned about the development of controllers able to receive dynamic feedback and weather variable inputs. Active and especially passive storage via the thermal mass of the building are discussed at length. Most modern attempts for energy management optimisation are considering in detail the trade-off between energy savings and occupant comfort as opposed to earlier controllers focusing exclusively to energy savings. A summary of the above findings can be seen in Fig. 16.

7. Discussion

Direct comparison of the reported accuracies in prediction of weather variables and energy consumption as well as the observed savings via optimisation algorithms is not particularly meaningful, as most of the techniques are relevant and tailored to specific

buildings and depend on the availability of data and required outputs. Hence, it is not simple to establish an absolute superiority of a specific group of techniques for the purpose of energy management in commercial buildings. Instead and as seen earlier, there are distinct advantages and disadvantages depending on the available resources, complexity and magnitude of each case where a forecasting algorithm is used to assist in energy management.

After reviewing the literature however, it is evident that ambient temperature, as well as humidity and solar radiation are the main factors of uncertainty in building energy consumption and generation. As such, the major finding from the analysis above is that the consideration of weather variable forecasting always produces enhanced accuracy compared to a deterministic approach of prediction and optimisation of the system with non-weather sensitive data.

A common technique that was seen in many case studies, involves predictions of temperature, which are then in turn applied to HVAC load forecasts and management of the set points or other DR measures, such as preconditioning or active storage. Such one-dimensional approaches impose constraints on the energy savings margins. For larger commercial buildings with a range of generation and management options additional weather variables are significant for the analysis of the energy system. However, the implementation of an energy system able to utilise several weather inputs appears to be problematic. The introduction of additional input variables increase the degree of complexity and in turn the required computational resources. Furthermore, weather variables require non-linear models that cannot be accurately designed using statistical methods. The incorporation of localised numerical weather forecasts allows accurate handling of non-linear models and while still there is an increase in complexity and cost of the energy system, we argue that the savings potential is promising.

So far, the literature has not considered the integration of a complete set of weather variable forecasting for commercial building energy management. Using a set of lightweight numerical prediction tools and statistical processing, we propose that a modular approach based on weather predictions is able to provide optimal results for the majority of aspects of energy management in certain commercial buildings. The framework of the proposed integrated architecture consisting of a three layer forecasting and optimisation system can be seen in Fig. 17. The interdependencies between modules of successive layers have been established in the literature and reviewed in the sections above. A framework such as the one shown in Fig. 17 is meaningful for commercial buildings with enhanced energy generation and management capacity, so that the potential added savings can justify the increased model cost.

The main advantage of this modular approach is the added value in a range of building energy management components of the higher tier. The uninterrupted flow of inputs and outputs from each layer to the next, the compatibility of data formatting and tailored control over all aspects of energy management are also noteworthy benefits. Since the uncertainty associated with weather variables propagates towards the higher levels, it is important to be able to have access to reliable forecasts for the range of variables required for different horizons, preferably localised. Weather variable predictions in level 1 feed into higher level modules and assist with the respective predictions. Temperature is the most important variable and can be predicted using a time series or a NN approach especially for short horizons; however, NWP models are favourable for such an integrated framework as they can predict factors like solar radiation, humidity, wind speed and direction and cloud formation that contribute to the system's performance.

Level 2 consists of modules related to load and availability of energy. Energy generation forecasts from RES are useful for managing peak and base loads as well as energy flows to and from the grid. Passive energy storage in the thermal mass of the building can also be modelled towards the same end. Other important parameters depending on weather forecast outputs include solar heat gains and occupant comfort. In addition, climate evolution prediction may be possible, which is useful for future planning and upgrading. At this level, electricity pricing is considered as a major non-weather dependent component subject to forecasting.

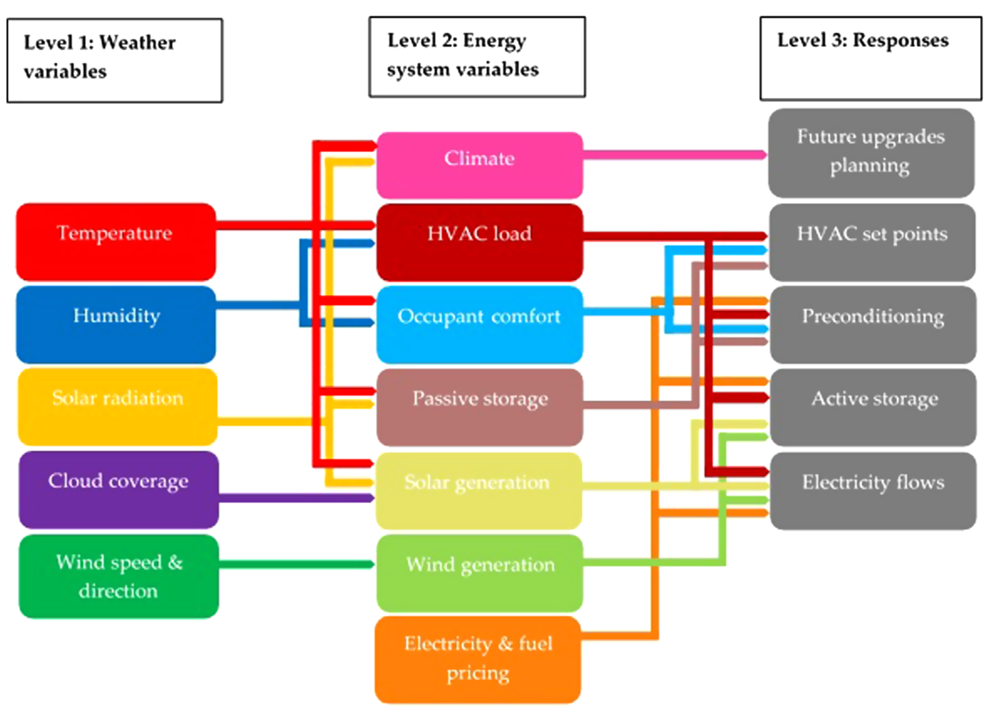


Fig. 17. Proposed integrated weather, load and generation forecasting architecture for energy system optimization.

Level 3 consists of the energy management optimisation framework, typically a holistic MPC. Besides HVAC operation optimisation, active storage where available such as batteries or ice storage, is relying on inputs from the previous layer. Electricity flows within the building (from DG sources to load and/or storage) as well as exchange with the grid can be planned accordingly. External factors that need to be considered include the building type, size, equipment and occupancy patterns. The cost of the complexity of the system and higher spatial and temporal resolutions should always be weighed against the potential savings in each layer.

8. Conclusion

The aim of this review was to investigate the multiple dimensions and value of forecasting and energy optimisation algorithms for commercial building energy systems, with emphasis on those with weather variable inputs. While annual or longer horizon forecasting is certainly valuable for planning upgrades and policies, most building management systems are focusing on short term load forecasting and high resolution dynamic optimisation. A review of forecasting concepts was conducted and complemented by a thorough discussion of relevant studies in the literature for weather, generation and load forecasting for commercial buildings as well as their applications in energy management.

It was found that weather variables are significant components of the evolution of building energy systems and minimising the uncertainty in predicting their evolution can lead to significant savings, usually in the range of 15–30% compared to a deterministic and non-weather sensitive control approach. For smaller building systems with limited optimisation components, simple statistical processing of archived data or even external forecasts of temperature are sufficient for energy management. For larger and more dynamic building energy systems, it was found that the availability of accurate weather forecasts greatly enhances the savings potential. Commercial buildings with such capacity can benefit from integrated weather forecasting frameworks as there are dynamic interactions between individual components of the weather inputs, the system and the grid. While most approaches utilise temperature forecasts, it is evident that additional factors contribute to different extents to energy management and optimisation. So far there are no practical lightweight models towards that end in the literature. Hence, we argue that integrated weather forecasts are vital and may potentially generate additional savings, especially where generation from renewable energy sources or passive thermal storage are available.

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